

---

# Towards Managerial Support for Data Analytics Results

---

Uroš Bole<sup>1</sup> and Gregor Papa<sup>2,\*</sup>

<sup>1</sup>*Glarminy.com, Slovenia*

<sup>2</sup>*Jožef Stefan Institute, Ljubljana, Slovenia*

*Email: gregor.papa@ijs.si*

*\*Corresponding Author*

Received 12 July 2019; Accepted 17 March 2020;  
Publication 15 June 2020

## Abstract

Studies of analytics integration management have largely focused on executive-led analytics at the enterprise level. However, in most organizations analytics initiatives do not enjoy executive support at the outset. Top management must first be convinced of the benefits, which slows down the path to competing via analytics. To successfully win top management support for broader analytics implementation an analytics pioneer should achieve five key aims: patiently build trust, manage interdisciplinary collaboration, focus on the problem solving action, facilitate the process, and importantly provide strong support to the embryonic analytics initiative. This is demonstrated through multiple-case study, presented in this paper. In embryonic analytics initiatives, the analytics champion appears locally, at mid-management level, and is up against the complex task of overcoming the resistance of an established organization, with its existing people, processes, data, technology, and culture. We examined what could be learned about the management of people-related issues in embryonic analytics processes. We studied the approaches used and lessons learned by all significant groups of stakeholders with the aim of helping managers show the value of analytics to their executives and colleagues.

*Journal of Industrial Engineering and Management Science, 2020, 1–16.*

doi: 10.13052/jiems2446-1822.2020.001

*This is an Open Access publication. © 2020 the Author(s). All rights reserved.*

**Keywords:** Data, analytics, data mining, collaboration, support, stakeholders.

## 1 Introduction

According to [1] “*Changing the way people think, interact with one another and perform their jobs is hard, and much harder than developing the technology expertise behind analytics sophistication.*”

Although organizational interest in analytics continues to grow [2–4], its implementation has been lagging [5, 6]. Studies of analytics integration management have largely focused on executive-led analytics at the enterprise level [4, 7, 8]. However, in most organizations analytics initiatives do not enjoy executive support at the outset. Top management must first be convinced of the benefits [7], which slows down the path to competing via analytics. This “prove-it” route leads to a series of projects that form a cyclical process. The iterations of this process consist of finding a business problem that can benefit from analytics, implementing a localized project to show its benefits, documenting and propagating the benefits, and iterating back to a new problem until executive sponsorship for broader implementation is secured. In such “*embryonic analytics*” initiatives, the analytics champion appears locally, at mid-management level, and is up against the complex task of overcoming the resistance of an established organization, with its existing people, processes, data, technology, and culture [7]. Most studies on analytics management do not go beyond this finding. Yet, unless an analytics pioneer possesses a good understanding of the issues related to changing the way people think, interact, and perform, analytics will remain an untapped source of competitive advantage in many organizations.

We therefore set out to examine what could be learned about the management of people-related issues in embryonic analytics processes. We studied the approaches used and lessons learned by all significant groups of stakeholders with the aim of helping managers show the value of analytics to their executives and colleagues. The findings can be expressed in the following five highly interdependent guidelines: (1) bear in mind that it is the first analytics initiative for all stakeholders, and build trust and commitment patiently; (2) appreciate cognitive differences among the stakeholders and achieve unity of effort by managing interdisciplinary collaboration; (3) maintain focus on the problem solving action to avoid the pitfalls of an explorative, emerging knowledge process; (4) carefully chose a process facilitator if the

organization's capacity to adopt analytics is not high; and (5) support the initiative as much as possible.

The rest of the paper is organized as follows: Section 2 presents the outline of the research on embryonic analytics; Section 3 is about building trust among stakeholders; Section 4 describes the importance of multidisciplinary collaboration; Section 5 is about vision and focusing on the problem that is to be solved; Section 6 briefly presents the importance of the facilitators; Section 7 talks about supporting the initiative during the analytics process; and Section 8 brings some concluding remarks.

## **2 Details of Research on Analytics**

This investigation aimed to identify the issues, actions, and problems that business people face when pioneering analytics without top management support. We attempted to distill what advice experienced analytics pioneers and other analytics stakeholders would give to those who are about to embark on such an adventure.

We use the term “analytics” as defined by Davenport and Harris [7]: the extensive use of data, statistical and quantitative analysis, explanatory and predictive models and fact-based management to drive decisions and actions.

The findings are based on data gathered through the case study research method. Ten organizations that recently introduced analytics participated in the multiple-case study. The organizations (more details in [9]) differ in four dimensions important for the generalizability of our findings:

- Geography – Argentina, Austria, Belgium, Canada, Germany, the Netherlands, Russia and Slovenia (in addition to the case study participants, we also interviewed four highly successful and experienced analytics consultants, two based in the USA, one in Germany and one in Canada).
- Size – fewer than 100 employees (1), 1,000-10,000 (4), 10,000-50,000 (4), over 100,000 (1);
- Economic sector – apparel, e-commerce, electronics, financial services, healthcare, law enforcement, pharmaceuticals, steel, and telecommunications; and
- Problems addressed with analytics – production scheduling, recommendation system, fraud detection, text mining, database marketing, quality control, process mining, product performance simulation, etc.

A total of 27 in-depth interviews lasting from one to two hours were conducted over a two-year period ending in summer 2012. They were carried out by the same researcher and were based on a purposefully constructed case study protocol and semi-structured interview guide with open-ended questions. The informants have been directly involved in embryonic analytics initiatives. Ten practitioners participating in the study have been analytics pioneers. To obtain additional, complementary perspectives on the subject, we also interviewed other significant stakeholders: analytics experts, domain experts, IT, and end-users. We stopped adding new case studies when theoretical saturation was reached. Some details on the interviews are summarized in table below.

**Table 1** Case study organizations

Organization	Geography	Size	Sector	Problems	No of interviews
ING	The Netherlands	>100,000	financial	database marketing	3
IMH	Russia	10,000–50,000	steel	quality control	2
E.G.O.	Germany	10,000–50,000	electronics	production scheduling	2
Telekom Austria	Austria	10,000–50,000	telco	database marketing	2
Gorenje	Slovenia	10,000–50,000	electronics	product performance simulation	2
GZA Hospitals	Belgium	1,000–10,000	non-profit	process mining	2
Amsterdam Police	The Netherlands	1,000–10,000	governmental	text mining	2
Domel	Slovenia	1,000–10,000	electronics	product lifetime prediction	3
MercadoLibre	Argentina	1,000–10,000	e-commerce	recommendation system	2
UCS	Slovenia	<100	apparel	recommendation system	3
Analytics consultants	The USA, Canada, and Germany	N.A.	various	various	4

### 3 Building Trust and Commitment Patiently

The importance of the trust is high, *“Everything in these projects is trust related. That is the secret to success. If you run into problems, which will always occur, you need to have a trusted relationship so that you can work together to overcome these problems.”* [10].

One recurrent source of conflict and failure is the often forgotten (albeit obvious) fact that the first analytics initiative in a corporation tends to be everyone’s first experience with implementing analytics. For you (the analytics champion) this implies that your comprehension of analytics (statistics, forecasting, predictive modeling, stochastic optimization, or simulation) is likely to be rather abstract. Your expectations about the benefits and the process may be unrealistic or erroneous, which is potentially frustrating for both you and the analytics expert. One analytics consultant commented: *“It astonishes me, how often the client says: What should we do next? This is the first for them and they are hesitating. Frequently they will also say: Do you have the data? ... and we say: No, our value is the service – the analytics. We can advise you on how to get the data... I think they would like to get a complete solution with a bow tie around it.”* [10].

To make things more complex, the analytics experts are unable to plan out the process beyond providing a very general framework which is often more vague than you would wish.

Given that it is an early analytics initiative, they are likely new to the organization. This means that they lack an understanding of some factors that significantly influence the analytics process, i.e. the organization’s business model, culture, and people. In this light, another consultant, who has focused on database marketing for more than 20 years, commented: *“We do a lot of work for [company name]. What we need to understand is how marketing works for their business, how they are selling products. It is not enough to know some marketing principles. It is more the understanding of the mechanics of [company name], how they sell chocolate or baby food, how the different components work together.”* [10]. Clearly, the path to solutions and their quality will greatly depend on organizational factors which analytics experts cannot know at the outset. This explains why even the most experienced analytics experts cannot give specific details about the analytics process.

At the start of analytics initiatives, the relationship among stakeholders (business champion, analytics expert(s), and often also domain expert(s), end user(s), and IT) hasn’t yet been built. This implies uncertainty. Experienced

practitioners recommend patience and persistence. Expect many questions and erroneous suppositions. Answering the first, and detecting and correcting the latter, may be time-consuming and sometimes frustrating and may lead to wariness. However, with time, mutual appreciation of the other's expertise will develop and result in mutual trust. In addition, stakeholder confidence in analytics will grow as its relevance to their work becomes clearer. Ultimately stakeholders need to develop commitment to analytics because, *“when you are deploying something, if it threatens anybody, they might be working hard to cause it to fail. That hurdle is always harder than it looks. Even if you successfully implement something and the users are not using it, then it is a dead end.”* [10].

Another related lesson shared by many practitioners is to avoid the temptation to immediately show analytics results when meeting larger groups of stakeholders. It is a common misconception that the analytics results and related benefits will immediately win everyone over. This rarely happens, particularly in early analytics initiatives. Team members entering into such a meeting tend to be cautious, and sometimes defensive, due to their uncertainty about analytics. For them it is a new and unknown way of doing things, and they are still trying to find out exactly how it will change their work life. Their true concerns rarely surface in larger meetings. Instead, the cumulative defensiveness of stakeholders easily erupts in emotionally-charged attacks on analytics.

It is therefore much more effective to share the results with stakeholders individually. In such a setting real fears are more likely to be openly discussed. With their insecurities addressed, stakeholders start to contribute their knowledge and slowly adopt the analytics solution as “their own”. This leads to commitment. When all or most stakeholders reach this point of identification with the analytics solution, a larger meeting with all stakeholders may be constructive. Experience has demonstrated time and again that the individual approach is the most effective one and in the end much faster than trying to win everyone over at once.

#### **4 Managing Interdisciplinary Collaboration**

Problems associated with interdisciplinary collaboration were by far the most frequently cited in our interviews. Analytics initiatives require a combination of business and analytics expertise which is difficult to find in one person, particularly in embryonic initiatives. This is because, like other professions,

advanced analytics requires a high degree of specialization. Consequently, analytics initiatives are necessarily interdisciplinary.

The source of difficulty in multi-disciplinary collaboration is in mental models. Different mental models are at the root of the differences in the way we see, comprehend, express, approach, and solve problems. Mental models are a set of basic assumptions about the world and how it works and depend on a person's cultural, educational, and professional background [11]. The more diverse these are, the more difficult interdisciplinary communication and collaboration are, the result often being conflict and failure. Early DM initiatives are particularly vulnerable. One experienced analytics champion from a financial services group explained: "*When you have new stakeholders, you have the feeling that you are in line, but you discover later that it is not exactly the reality!*" [10].

However, different mental models should be a source of creativity in problem solving. Different ways of thinking are better thought of as complementarity. This change in perception must be managed. Constructive interdisciplinary collaboration calls for the development of shared ways of thinking, or shared cognition [12, 13]. The more developed the shared cognition, the more effective and efficient joint efforts become as communication improves and mutual confidence and trust grow. This process requires coordination to enable stakeholders with different expertise to resolve their disagreements and achieve unity of effort [14, 15]. In particular, it helps the stakeholders understand that most conflicts stem from differences in ways of thinking (their complementarity), which may be a source of constructive conflict, rather than from personal or relationship conflict, which tends to be destructive [16].

The process of an individual's knowledge becoming part of the solution to a complex problem, from being in the mind of one person to becoming a team's constructed knowledge, is an iterative, dynamically evolving process with no ideal structure. It requires:

- externalization of tacit knowledge (mental models),
- its internalization by the remaining team members, and
- the negotiation of meaning in order to arrive to a common understanding.

When this level of shared thinking is reached it can become the basis for constructive interdisciplinary problem solving. Both the problem definition and the search for a solution are likely to undergo this process and therefore evolve as stakeholders develop shared cognition and a common

understanding of the problem [12, 13, 15]. In order to build a group that can think together, generatively and creatively, the literature on interdisciplinary collaboration suggests the use of Dialogue [17–19], a method for complex, interdisciplinary problem solving.

Practitioners affirm that the interdisciplinary learning process is greatly facilitated when there is mutual respect based on the awareness of one’s own ignorance – an analytics expert cannot know as much about the domain as a domain expert does, and vice versa. Another practical way to encourage interdisciplinary cooperation suggested in our study is to stimulate frequent interactions among the stakeholders through rapid prototyping or by breaking longer projects into shorter ones. The objective is to promote interdisciplinary learning and to manage expectations via frequent interactions rooted in the problem and emerging solutions. Frequently-given advice is to take advantage of effective visualizations and refrain from technical language; another important lesson is to remain silent as soon as the first end user or domain expert grasps the idea: *“If one has understood it, then he or she can perfectly explain it to his colleagues. Better than me because they are speaking a different language! I am not speaking their language. They have a different language they use, quite a different language!”* [10].

## **5 Focusing on the Problem Solving Action**

Developing an awareness of cognitive differences also helps one understand the concept of evolving problem definitions and solutions. Further, it reveals why the analytics problem definition process is uncertain and requires iterations. After a reflection on all of her experience, one interviewee who has pioneered analytics in logistics, energy, banking and telecommunications organizations explains that *“a typical failure is when, far into the project, you realize that you have done something that was not required. There was a hidden demand and you did not spend enough time to make sure that you were in line with what was being requested.”* [10].

Managing the analytics process requires an explorative, experimental approach. The path is often unclear because the requirements are often uncertain and changing. The technical problem identified to be solved can be quite different from the true business problem, which often can only be approximated, especially with the limited data usually available. One must answer the question: How can analytics help solve the business problem? This may be difficult to answer before a healthy level of common understanding is reached. Perhaps also the algorithms needed are non-existent or unknown

to the team. Therefore, while project planning and management with time-lines, milestones, and pre-defined deliverables are necessary to some degree, they cannot be binding as in an engineering or business intelligence project [20–22]. In such contexts, IS and project management literature favours an adaptive, agile approach with less detailed planning and requirement specifications, and an experimental and evolutionary design with significant on-going learning and changes [23–25].

A failure to arrive at a common understanding may emerge anywhere in the process. For example, a commonly reported difficulty for an analytics expert is to go off-track by unconsciously making domain-related assumptions that had not been addressed explicitly by the domain expert. Contrary to what is often perceived, this is not a consequence of information being intentionally withheld. Rather, due to their unfamiliarity with analytics, domain experts cannot know a priori which pieces of information might be relevant. Analogously, business people have often been reported to go astray by designing tests or other plans of action which ignore important analytics-related suppositions.

To remedy this situation additional communication is recommended. However, it does not always help. The unfortunate circumstance is that often these unconsciously made suppositions can only be discovered by the other party once they materialize in analysis results, a model, or action. Hence, to maintain the desired focus and avoid delays, practitioners also recommend holding frequent meetings where outputs or plans of action are reviewed together by business people and analytics experts. This means that a linear analytics process (in terms of the business side providing the data and describing the problem in one meeting and expecting the analytics expert to come back with a solution in a few weeks) is unlikely to yield satisfactory results. Analytics consultants reaffirm this claim by drawing on all their experiences. They suggest that client satisfaction tends to be conditioned on their prior disposition to engage in a longer (some months) problem-solving collaboration. Unfortunately, most business people still expect and demand a linear analytics process.

When you start an analytics initiative, you will normally have a vision and an aim. Yet maintaining the right focus will require constant effort. Many of our interviewees recommend staying focused from the beginning of the initiative on the action that will solve the selected business problem. If you do not take this advice, you will have to learn it the hard way. You are likely to eventually deliver anyhow, but the earlier you learn to constantly keep your eye on the problem solving action, the fewer iterations

that will be required. This is the best way to increase the speed to actionable solutions.

## **6 Facilitating the Process**

Process facilitation either makes or breaks an embryonic analytics initiative. Its conscientious management is particularly important in traditional organizational cultures not accustomed to fact-based decision making and interdisciplinary collaboration. Surprisingly, in the organizations we studied, this role was not always carried out by the analytics pioneer. The primary contribution of process facilitation is to *make analytics work by putting everything in its place*". In particular, stakeholder trust and commitment is secured through interdisciplinary collaboration management and by ensuring that all involved are focused on the problem solving action.

In some organizations process facilitation is taken care of by organizational culture which is rooted in fact-based decision-making and interdisciplinary collaboration. Examples might include younger high-tech companies or specific departments in otherwise traditional organizations, e.g. marketing or R&D. However, such organizations are rare. As was the case in our study, DM integration success in most organizations depends on the ability of one team member to facilitate the process.

Our data shows that process facilitation may be carried out by any stakeholder: the analytics pioneer, an analytics expert, a domain expert, or an IT expert. The most outstanding characteristic of process facilitators is that they know the organization and how it works in order to set things up for success. To be able to deliver, they should enjoy a considerable level of authority among the stakeholders and know them well. In turn, the stakeholders would ideally consider the process facilitator to be impartial when dealing with people from different departments. In this light, facilitators should have good interpersonal skills, emotional intelligence, and understand the implications of interdisciplinary collaboration. They should also exhibit a predisposition for business development and maintain focus on the actionability of proposed solutions. Some facilitators are able propagators of analytics and its benefits throughout the organization and especially towards the top. In addition, the most driven continuously scout the organization in search for new analytics-related problems and potential allies, i.e. future analytics champions in order to convince them to pioneer analytics in their part of the business.

In none of the ten cases we studied was the appointment of a process facilitator intentionally managed. However, leaving process facilitation up to chance is risky. Our data shows that DM initiatives without a process

facilitator in organizations with unfavorable corporate cultures fail. In other cases, months or even years (three years in one example) were lost with no significant progress in terms of analytics benefits until a process facilitator spontaneously appeared. It therefore pays to consider the issue, particularly if you judge that you will not be able to facilitate the process yourself.

## 7 Supporting the Initiative

The analytics champion is a person within the organization who understands the potential of analytics, has a business problem that may be solved with the use of analytics, supports the embryonic analytics process, and promotes analytics internally [7]. Champions provide information, resources, and support. They achieve executive commitment by pushing for fact-based decision-making, through their people skills, by teaching others, by focusing analytics efforts where they make the most difference, etc. [8].

Even if you have chosen a different person to facilitate the analytics process, your support to the initiative will be critical. Analytics consultants who had been involved in many early initiatives attest: “*We have had cases when the champion has left the company and the project just slowly stalls.*” [10]. This is due to the fact that the analytics champion “*is the person with the highest interest in the success of a project, who puts his head down and says: I’ll make sure that this is a success. Otherwise these kinds of projects never end.*” [10]. Moreover, you are likely to be in the best position to show and propagate analytics benefits to the rest of the organization and its board “*saying this is the impact we made*”.

Initiatives without an engaged analytics champion were not successful. For instance, one manufacturer had successfully carried out their first simulation project and intended to implement others. Their plans never materialized because the analytics champion moved to another company. Hence, an analytics champion plays two key roles: initiating an embryonic analytics process and facilitating it. Our study also showed that an analytics champion cannot always actively manage the such processes, and then it is vital to delegate process facilitation.

## 8 Conclusion

To successfully win top management support for broader analytics implementation an analytics pioneer should achieve five key aims: *patiently build trust, manage interdisciplinary collaboration, focus on the problem solving action, facilitate the process, and importantly provide strong support to the*

embryonic analytics initiative. This was demonstrated by our multiple-case study. Two of the ten early analytics implementations we investigated were unsuccessful in obtaining top management support. Analysis of their guideline observance shows failure in at least one of the dimensions. At the other extreme, there were three initiatives that followed all five guidelines from the start. Their analytics champion was actively involved in the management of the process; hence, they quickly gained top management support for analytics. Similar success was occurring in two other organizations that were still in the midst of the embryonic analytics process. They were making rapid progress towards executive support for analytics because the five guidelines were observed from the outset.

The remaining three cases are particularly interesting because they demonstrate the importance of *process facilitation*. In these three organizations the analytics champion initiated the embryonic analytics process, but could not actively manage it. No notable benefits were achieved until one stakeholder took up the process facilitation role. Several months (years in one example) were lost getting to this stage where real progress could finally begin. From then on, all three initiatives showed radical improvement in implementation and propagation of analytics benefits. Finally, top executive support was achieved which put these organizations in a position to build a broader analytical capability for enterprise-wide competition via analytics.

## Acknowledgement

The authors acknowledge the financial support from the Slovenian Research Agency (research core funding No. P2-0098). Operation was also part financed by the European Union, European SocialFund.

## References

- [1] Kiron, D., and R. Shockley. 2011. Creating Business Value with Analytics. *MIT Sloan Management Review*, vol. 53, no. 1:56–63.
- [2] Gartner. 2017. Gartner Identifies the Top 10 Strategic Technology Trends for 2018, <https://www.gartner.com/en/newsroom/press-releases/2017-10-04-gartner-identifies-the-top-10-strategic-technology-trends-for-2018>.
- [3] Luftman, J. and T. Ben-Zvi. 2010. Key Issues for IT Executives 2010. *MIS Quarterly Executive*, vol. 9, no. 4: 263–273.

- [4] LaValle, S., E. Lesser, R. Shockley, M.S. Hopkins and N. Kruschwitz. 2011. Big Data, Analytics and the Path From Insights to Value. *MIT Sloan Management Review*, vol. 52, no. 2: 21–32.
- [5] Rexer, K., 2011. *4th Annual Data Miner Survey – 2010 Survey Summary Report*, <https://www.rexeranalytics.com/Data-Miner-Survey-Results-2010.html>.
- [6] Rexer, K., 2012. *5th Annual Data Miner Survey – 2011 Survey Summary Report*, <https://www.rexeranalytics.com/Data-Miner-Survey-Results-2011.html>.
- [7] Davenport, T.H., and J.G. Harris. 2007. *Competing on Analytics: The New Science of Winning*, HBS Press.
- [8] Davenport, T.H., J.G. Harris, and R. Morison, 2010, *Analytics at Work: Smarter Decisions, Better Results*, HBS Press.
- [9] Bole, U., A. Popoviè, J. Žabkar, G. Papa, and J. Jakliè. 2015. A case analysis of embryonic data mining success. *International Journal of Information Management*, vol. 35: 253–259.
- [10] Bole, U., 2013. *Transcripts of semi-structured interviews with data mining practitioners*. JSI Technical report, no. 11355, Ljubljana.
- [11] Senge, P.M., 2006. *The Fifth Discipline: The Art and Practice of the Learning Organization*, Doubleday.
- [12] Beers, P.J., H.P.A. (Els) Boshuizen, P.A. Kirschner and W.H. Gijssels. 2005. Computer Support for Knowledge Construction in Collaborative Learning Environments. *Computers in Human Behavior*, vol. 21, no. 4: 623–643.
- [13] Du Chatenier, E., J.A.A.M. Versteegen, H.J.A. Biemans, M. Mulder and O. Omta. 2009. The Challenges of Collaborative Knowledge Creation in Open Innovation Teams. *Human Resource Development Review*, vol. 8, no. 3: 350–381.
- [14] Lichtenstein, S., D. Bendall, and S. Adam. 2008. Marketing Research and Customer Analytics: Interfunctional Knowledge Integration. *International Journal of Technology Marketing*, vol. 3, no. 1: 81–96.
- [15] Markus, M.L., A. Majchrzak, and L. Gasser. 2002. A Design Theory for Systems That Support Emergent Knowledge Processes. *MIS Quarterly*, vol. 26, no. 3: 179–212.
- [16] Holland, S., K. Gaston, and J. Gomes. 2000. Critical Success Factors for Cross-functional Teamwork in New Product Development. *International Journal of Management Reviews*, vol. 2, no. 3: 231–259.

- [17] Isaacs, W.N., 1993. Taking Flight: Dialogue, Collective Thinking, and Organizational Learning. *Organizational Dynamics*, no. Winter (1993):24–39;
- [18] Bohm, D., 2006. *On Dialogue*. Routledge.
- [19] Senge, P.M., 2006. *The Fifth Discipline: The Art and Practice of the Learning Organization*, Doubleday.
- [20] Hermiz, K., 1999. Critical Success Factors for Data Mining Projects. *Information Management Magazine*, <http://www.information-management.com/issues/19990201/164-1.html>.
- [21] King, E.A., and T.A. Rathburn. 2010. 101 Ways to Sabotage Your Predictive Analytics Project, Here Are the Top Five. *BeyeNETWORK*, <http://www.b-eye-network.com/view/13685>.
- [22] Viaene, S., and A. Van Den Bunder. 2011. The Secrets to Managing Business Analytics Projects. *MIT Sloan Management Review*, vol. 53, no. 1:64–70.
- [23] Highsmith, J., 2009. *Agile Project Management: Creating Innovative Products*, Addison-Wesley.
- [24] Gemino, A., B. Horner Reich, and C. Sauer. 2008. A Temporal Model of Information Technology Project Performance, *Journal of Management Information Systems*, vol. 24, no. 3: 9–44.
- [25] Howel, D., C. Windahl, and R. Seidel. 2010. A Project Contingency Framework Based on Uncertainty and Its Consequences, *International Journal of Project Management*, vol. 28, no. 3: 256–264.

## Biographies



**Uroš Bole**, obtained his B.Sc. in Applied Mathematics and Economics from Brown University (1996), MBA from IESE Business School (2000) and a Ph.D. from Jožef Stefan International Postgraduate School (2013). His Ph.D. research revolved around the integration of data mining in organizations.

His research interests span interdisciplinary collaboration, systemic thinking, business process reengineering, organizational learning, and process consultation. He is a co-founder of a startup providing data mining and stochastic optimization solutions, and an owner of Glarminy.com, a platform for exchange of ideas.



**Gregor Papa**, is a senior researcher at the Jožef Stefan Institute, Ljubljana, Slovenia and an Associate Professor of Computer Science at the Jožef Stefan International Postgraduate School, Ljubljana, Slovenia. He holds B.S. (1997), M.Sc. (2000) and Ph.D. (2002) degrees from the Faculty of Electrical Engineering, University of Ljubljana. His current research interests include optimization techniques, metaheuristic algorithms, and hardware implementations of high-complexity algorithms. His work is published in several international journals and conference proceedings.

